MACROECONOMIC FACTORS AND OIL FUTURES PRICES: A DATA-RICH MODEL

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This version: February 10, 2009

Abstract

I study the dynamics of oil futures prices in the NYMEX using a large panel dataset that includes global macroeconomic indicators, financial market indices, quantities and prices of energy products. I extract common factors from these series and estimate a Factor-Augmented Vector Autoregression for the maturity structure of oil futures prices. I find that latent factors generate information that, once combined with that of the yields, improves the forecasting performance for oil prices. Furthermore, I show that a factor correlated to purely financial developments contributes to the model performance, in addition to factors related to energy quantities and prices.

KEYWORDS: Crude oil, futures markets, factor models.

JEL CLASSIFICATION: C53, D51, E52.

*Department of Economics, Stockholm University, pzaga@ne.su.se. This work started when I was a visiting scholar in the Research Unit of the Bank of Finland, and was completed during a consultancy assignment for the Research Department of Sveriges Riksbank. I acknowledge the warm hospitality of both institutions. I am deeply grateful to Vincent Brousseau and Tarja Yrjölä for help in constructing the dataset. Efrem Castelnuovo, Juha Kilponen, Massimiliano Marzo and Alistair Milne contributed with relevant suggestions and constructive criticism. The usual disclaimer applies.

1 Introduction

During the past year, oil prices have made the headlines of the financial press almost every day. Since the beginning 2008, the spot price of crude oil traded in the New York Mercantile Exchange (NYMEX) has almost doubled at peak. This has raised serious concerns among market participants and policymakers worldwide. Comments released to the press have often denoted a deep disagreement on the causes of the price spikes and, in general, on the mechanics of oil market.

Bernanke (2008) has represented the central bankers' view in a timely manner, stating that

> "...the price of oil has risen significantly in terms of all major currencies, suggesting that factors other than the dollar, notably shifts in the underlying global demand for and supply of oil, have been the principal drivers of the increase in prices. (...) Another concern that has been raised is that financial speculation has added markedly to upward pressures on oil prices. (...) However, if financial speculation were pushing oil prices above the levels consistent with the fundamentals of supply and demand, we would expect inventories of crude oil and petroleum products to increase as supply rose and demand fell. But in fact, available data on oil inventories show notable declines over the past year."

Trichet (2008) clarifies the role that factors unrelated to energy demand and supply can play in oil markets:[1]

> "I am not sure that speculation is the major culprit for what we are observing. The major issues are associated with supply and demand.... It is not the futures market itself that is the problem. The problem is that this is across-the-board reallocation of portfolios that gives more weight to commodities in general."

Since oil commodities are traded through futures and derivatives contracts, market views shape the pricing of oil commodities. In this sense, the financial press has pushed the hypothesis that purely financial factors, or 'speculation', have been behind the recent spikes (see Chung, 2008 and Mackintosh, 2008).

The academic literature on the macroeconomics of oil prices presents the same dichotomy. For instance, Kilian (2008b) suggests that a proper measurement of the business cycle effects of energy prices requires disentangling the role of demand supply shocks in energy markets. Kilian (2008a) decomposes the real price of crude oil into supply shocks,

[1] Also quoted in Barber (2008).

shocks to the global demand for industrial commodities, and demand shocks that are idiosyncratic to the oil market. The role of energy quantity factors is stressed also in Alquist and Kilian (2008), who show that spread between oil futures prices of different maturities are related to uncertainty about supply shortfalls.

The literature on the financial determinants of oil prices has produced a number of results on the role of uncertainty for oil pricing. Askari and Krichene (2008) model the jump intensity of daily crude oil prices between 2002 and 2006. They find that measures of market expectations extracted from call and put option prices have incorporated no change in underlying fundamentals in the short term. Chong and Miffre (2006) document the presence of a significant pattern of risk premia earned by investors on a number of commodities futures since 1979, including crude oil. Gorton, Hayashi and Rouwenhorst (2007) show that, although commercial positions on oil futures are correlate with inventory signals, they do not determine risk premia. Finally, Marzo, Spargoli and Zagaglia (2009) examine the predictive content for futures prices of a specific type of oil derivative contract, namely oil spreads. Their results indicate that oil spread prices have stable predictive power for futures prices, thus supporting the hypothesis that speculative motives matter.

A number of key questions related to price formation in oil markets is not dealt with in the literature. The issue of causality between spot and futures prices across the maturity structure is largely unsettled. Suppose that oil futures contain information about spot prices. Omitting futures prices would bias the results in favour of a strong role for demand-supply factors to drive the spot price. It is not clear what the channels are for oil prices to have macroeconomic impact. Moreover, the role of macroeconomic factors for the dynamics of oil prices has been studied in isolation from the conditions prevailing in financial markets. This is at odds with what is suggested by Trichet (2008) with reference to recent episodes.

In this paper, I exploit the information from a large panel of energy prices and quantities, macroeconomic and financial data to study the dynamics of the term structure of futures prices for crude oil. I assume that the available time series are noisy measures of broad concepts, such as demand and supply. Hence, I treat these variables as unobservable. Like Bernanke, Boivin and Eliasz (2005), I extract common factors. I model the joint dynamics of the factors and the oil prices in a 'Factor-Augmented' vector autoregression (FAVAR).

This modelling strategy has already been applied by Mönch (2005) to construct a no-affine model for the yield curve of government bonds. There are multiple advantages from following this approach. The first one is that this can capture the underlying dynamics in oil prices generated by latent factors of different nature. The FAVAR allows to model the relevant maturity spectrum of oil futures prices in a flexible way.

The panel dataset from which I extract common components include over 200 data series with detailed information on energy demand and supply, energy prices, macroeconomic and financial variables. I show that a latent factor correlated with the open interest on oil futures prices contributes significantly to the joint model of the yields. This appears to corroborate the conjecture of Trichet (2008) on the financial determinants of oil prices. The other factors are strongly correlated with data on energy quantity and prices, as typically suggested by the macroeconomics literature. I find that augmenting the information from the term structure of oil futures prices with latent factors improves the forecasting performance of the model.

This paper is organized as follows. In section 2, I outline the structure of the FAVAR model. Section 3 presents the dataset. Section 4 describes the results. Final remarks are presented in section 5.

2 The Factor Augmented VAR Model

The model presented here is based on the assumption that the futures price for one maturity is driven both by the prices of the other maturities, and by macroeconomic shocks. The macroeconomic determinants are proxied by unobservable factors that summarize the common information in a large number of time series. The joint dynamics of the observable an unobservable variables in modelled in the FAVAR model of Bernanke, Boivin and Eliasz (2005).

The general form of the FAVAR can be written as

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \mu + \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \Sigma\ \nu_t \tag{1}$$

where $\Phi(L)$ is a $(k+m) \times (k+m)$ matrix of lag polynomials, ν_t is a $(k+m) \times 1$ vector of standardized normal shocks. $Y_t = [y_t', y_{t-1}' \ldots]$ is a vector $m \times 1$ of observed variables. The unobservable factors are collected in the $k \times 1$ vector $F_t = [f_t', f_{t-1}' \ldots]$. Equation 1 states that the dynamics of the factors is affected by its own lags, by the vector of observables, and by the shocks.

Equation 1 cannot be estimated without knowledge of F_t. For that purpose, a large number p of series can be used to extract common factors. The 'information series' are collected in the vector X_t with dimension $p \times 1$. The dynamic factor model of Stock and Watson (2002) can then be used to obtain F_t

$$X_t = \Lambda^f(L) f_t + \Lambda^y(L) y_t + \epsilon_t. \tag{2}$$

If $p > k$, and k is small, the dynamic model 2 can be rewritten as a static factor model with fixed loadings

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + \epsilon_t. \tag{3}$$

Bernanke, Boivin and Eliasz (2005) propose two methods for estimating the model 1-3. The first one is the 'diffusion index' approach of Stock and Watson (2002), which consists itself of two steps. In the first step, equation 3 is used to estimate the unobservable factors F_t through principal components analysis. The estimated $\hat{F}_t$ is then fit to the FAVAR model 1. The second method for the estimation of the model follows a single-step Bayesian likelihood approach. Bernanke, Boivin and Eliasz (2005) discuss a Gibbs sampler that approximates the marginal posterior densities of both the factors and the parameters. Since it is not clear a priori which estimation method delivers the results that are most desirable, Bernanke, Boivin and Eliasz (2005) estimate the model using both approaches, and find that they yield similar outcomes. In this paper, I apply the two-step procedure.

The asymptotic principal component method of Stock and Watson (2002) estimates the factors by recovering the space of X_t spanned by both F_t and Y_t. Denote by V the eigenvectors corresponding to the k largest eigenvalues of the variance-covariance matrix XX'/k. The estimates of the factors are obtained from

$$\hat{F} = \sqrt{T}V, \tag{4}$$

and the loadings are

$$\hat{\Lambda} = \sqrt{T}X'V. \tag{5}$$

3 The dataset

I use monthly data from January 1992 until March 2008 for a total of 193 observations for each series. The vector Y_t consists of returns on the spot price for WTI crude oil traded in the New York Mercantile Exchange (NYMEX), and on futures prices with maturities of 1, 6 and 12 months.[2] The panel dataset used for the extraction of the factors comprises 239 series that are meant to capture the macroeconomic, financial and geographic forces that move oil prices. The complete list of the series, the sources and the choice of filtering are reported in Appendix A.

Oil prices in the NYMEX respond to global supply and demand factors. Hence, the dataset includes series that are publicly available on petroleum stocks and consumption in the major OECD countries. Since this information is not available for the major emerging economies (Russia, India and China), the industrial production index is used as a proxy for consumption pressures. Instead, crude oil production data account for the entire range of oil producers worldwide. Almost half the series on energy quantities described in Appendix A refer to the U.S. In particular, there is detailed information on the use of all the available energy sources across sectors of the economy, including the energy products derived from

[2] Returns are computed as the first difference of the log.

petroleum and natural gas. There are indicators on rigging and drilling activities in the U.S., as well as on alternative sources of energy such as ethanol. I use around 50 price indices that are related with U.S. imports and refining. I control for the role of shipment prices to the Mediterranean sea and from the Gulf to Northern Europe.

The macroeconomic part of the dataset consists of on measures of monetary aggregates, prices indices, indicators of confidence and bilateral exchange rates for the U.S. economy. Since the stability of the Dollar exchange rate is often pointed to as a key factor for oil prices, I use the global hazard indicator of Brousseau and Scacciavillani (1999). This is a measure of risk in foreign exchange markets calculated from implied volatilities of currency options. Following the lead from the previous quotation of Bernanke (2008), the dataset includes information on the open interest and the volumes of traded futures contracts, as well as prices of crude oil spreads. In particular, crude oil spreads are over-the-counter derivatives. As Marzo, Spargoli and Zagaglia (2009) show, these contracts have predictive content for oil futures prices, and can provide information on the speculative motive for trading oil. Finally, the dataset comprises the prices of stocks of major oil companies, and a number of bond and stock indices.

4 Results

4.1 Model specification

In the first part of the estimation, I extract common factors from the panel dataset using static principal components along the lines of Stock and Watson (2002). The first 8 factors account for 80% of the variance in the dataset. Table 1 reports the fraction of variance explained by the first four factors. These factors account for a sizeable proportion of the total variation, namely around 50% . They exhibit a low degree of persistence. The estimated autocorrelation coefficients are however quite different across factors.

I include the first four factors in the FAVAR model for two reasons. Testing for the optimal number of factors using the statistical framework of Bai and Ng (2008) points in favour of the use of these factors. On more general grounds, the VAR model presents a tradeoff between parsimony and fit. Various experiments suggest that the results are qualitatively unaltered by the inclusion of additional factors.[3] A similar issue arises for the choice of the lag length. Information criteria suggest that 2 lags provide a reasonable specification of the model.

4.2 Factor estimates

The factors extracted from the panel have no structural interpretation unless identifying assumptions are imposed. In order to provide some understanding on the information they

[3]These results are available from the author upon request.

convey, I regress the factors on the variables of the panel. Table 2 reports the variance explained by the five series that are most correlated with the factors. The first factor is strongly correlated with a price index of crude oil imports. This can be interpreted as a cost indicator of the price pressure on oil futures. The second and third factors are related to stock volumes of oil-related products. This has to do with the intermediate demand for crude oil. Finally, the fourth factors is correlated with a purely financial variables that is disconnected from real developments in oil markets. This provides support to the claim that financial factors contribute to the determination of oil prices.

Figure 1 plots the estimated factors together with the most correlated series of the panel dataset. The factor loadings are plotted in figure 2. I break down the contribution to the loadings of each factor by three groups of series, divided into energy prices, energy quantities and macro and financial data. The contributions to the factors differ largely across series. Energy prices provide the largest contribution to the first factor. Energy quantities instead account for the largest weights in the second and third factors. Finally, macro and financial series determine the largest fraction of the fourth factor. These considerations support the economic interpretation of the factors discussed earlier.

4.3 Preliminary evidence on the role of factors

In order to understand the relation between the factors and the the return on oil futures prices at different maturities, I report the correlation between the yields and the lagged factors in Table 3. The correlations differ in terms of size and sign across factors. The first factor has a large and positive contemporaneous correlation with all the returns. This is consistent with the interpretation of measure of cost pressure on futures prices. The other three facts are less correlated with the yields. The sign of the contemporaneous correlation on the second and third factors is negative, in agreement with the idea that available stocks provide a buffer to prices. The third factor is however weakly correlated, with the magnitude of correlation increasing at longer lags. Overall, this preliminary evidence suggests that not all the factors have predictive power for the yields at various lags.

To explore further this issue, I estimate unrestricted regressions of the yields on the factors, which takes the form

$$Y_t = \mu + \Lambda F_t + \epsilon_t. \tag{6}$$

Table 4 reports the parameters estimates and the fraction of explained variation. Two observations arise. The first one concerns the fact that only the first and the fourth factors have statistically significant coefficients for regressions of all the yields. The estimated coefficients are the signs one would expect from the correlation analysis. The second consideration is that the regressions explain large fractions of the variation in the yields of up to 6 months of maturity. Moreover, the longer the maturity, the more limited the scope of the factors for explaining the dynamics of the yields. For 1-year oil futures, the joint predictive power of the factors becomes low, as the R^2 declines to approximately 12%.

4.4 Parameter estimates

Before estimating the factor-augmented VAR, I evaluate the persistence of all the variables. In order to investigate the null of a unit root, I run the tests proposed by Dickey and Fuller (1979) and Phillips and Perron (1988). Instead of relying on the standard formulation of these tests, I apply the state-of-the-art modifications proposed by Perron and Ng (1996, 2001).[4] Table 5 reports the test statistics. The results indicate that the null of a unit root is rejected for all the variables. Hence, all the series to be included in the FAVAR can be modelled as stationary variables.

The estimates of the FAVAR model are detailed in Table 6. The upper part of the diagonal of the coefficient matrix Γ_1 suggests that only the first fact displays a certain degree of persistence. Additional evidence on the relation between the factors and the returns can be obtained through pairwise Granger-causality tests in the VAR. These are F tests for zero restrictions on the lagged coefficients of a variable onto another. Table 7 reports the test statistics and the p-values for the null of Granger causality of the factors for the yields, and vice versa. The first panel shows that not all the factors have predictive power for the yields. In this sense, the most important factor is the first one. The second factor, instead, does not Granger cause any of the yields. Since these are bivariate tests, they provide no information on the indirect relation between variables. For instance, the second factor might Granger cause another factor, which can in turn have predictive power on the yields. Interestingly, the second panel shows that the yields Granger cause of the factors. This highlights one of the advantages of the modelling strategy pursued in this paper, namely capturing the interaction between the observable and non-observable variables.

Figure 3 plots the fitted series in-sample. The fitted series do not succeed in capturing the large variation that characterizes the historical data. However, they fit the peaks relatively well. In the case of the returns on 1-year futures, the model replicates the large swing of the sample that takes place in 1996-1998.

4.5 Out-of-sample forecasts

In this section, I compare the performance for out-of-sample forecasts from the FAVAR with that of alternative models. In particular, the competitor models are

[4] These are based on the use of Generalized Least Squares detrended data for the estimation of the spectral density matrix at zero frequency, and on the computation of a class of improved selection criteria for the choice of the order of the underlying autoregression. Perron and Ng (1996) shows that both aspects improve the small-sample properties of the tests.

- a VAR on yields only

$$\hat{Y}_{t+h|t} = \hat{\mu} + \hat{\Lambda} Y_t, \tag{7}$$

- a factor-only VAR

$$\hat{Y}_{t+h|t} = \hat{\mu} + \hat{\Lambda} F_t, \tag{8}$$

- a random walk

$$\hat{Y}_{t+h|t} = Y_t. \tag{9}$$

The forecasting exercise is run as follows. I initialize the parameter estimates on data until December 2002. The forecasts are then computed for various horizons, and the model estimates are updated recursively by estimating with one additional data-point at the time.

Table 8 reports the root mean squared errors (RMSE). Table 9 lists the squared errors relative to those of a random walk. The FAVAR generates the best forecasts for 1- and 3-month and 1-year yields at short horizons. The VAR with yields only is instead the best predictor for yields 6 months ahead. For forecast horizons longer than 3 months, the FAVAR generates the same squared errors of either the VAR with yields only or the factor-only model. However, the squared errors generated by the models are rather close. This means that no major reduction in RMSE are obtained from choosing the best performing model. To summarize, the joint information from factors and yields improves to a limited extent the predictive power for the yields at short horizons.

5 Conclusion

This paper models the dynamics of the term structure of oil futures prices by using information from a panel dataset including over 230 series with global macroeconomic indicators, financial market indices, quantities and prices of energy products. I estimate a Factor-Augmented Vector Autoregression with latent factors extracted from the panel. I show that latent factors generate information which, once combined with that of the yields, improves the forecasting performance for oil prices. Furthermore, I find that a factor correlated to purely financial developments contributes to the model performance, in addition to factors related to energy quantities and prices.

The results presented here can be extended in a number of directions. I am planning to use Bayesian model averaging to study the performance of the best-performing subset of factors for forecasting the term structure of oil prices. Moreover, the factors could be used to identity the impact of oil demand and supply shocks. In this sense, it would be important to understand what role purely financial market variables can play for the persistence and magnitude of the estimated shocks.

References

Alquist, Ron, and Lutz Kilian (2008), "What Do We Learn from the Price of Crude Oil Futures?," *unpublished manuscript*, University of Michigan.

Askari, Hossein, and Noureddine Krichene (2008), "Oil Price Dynamics (2002Ũ2006)," *Energy Economics*, 30(5), 2134-2153.

Authers, John (2008), "The Short View: Oil and US banks," *Financial Times*, July 23.

Bai, Jushan, and Serena Ng (2008), "Determining the Number of Factors in Approximate Factor Models," *Econometrica*, 70(1), 191-221.

Barber, Tony (2008), "Trichet rejects oil price link to trading," *Financial Times*, June 25.

Bernanke, Ben S., Jean Boivin, and Pitr Eliasz (2008), "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach," *Quarterly Journal of Economics*, 120(1), 387-422.

Bernanke, Ben S. (2008), "Semiannual Monetary Policy Report to the Congress Before the Committee on Banking, Housing, and Urban Affairs," U.S. Senate, Washington, July 15.

Brousseau, Vincent, and Fabio Scacciavillani (1999), "A global hazard index for the world foreign exchange markets," *ECB Working Paper*, No. 1.

Chong, James, and Joelle Miffre (2006), "Conditional Risk Premia and Correlations in Commodity Futures Markets," *unpublished manuscript*, EDHEC Business School.

Chung, Joanna (2008), "Fund accused of manipulating oil price," *Financial Times*, July 24.

Dickey, D. A., and W. A. Fuller (1979), "Distribution of the Estimators for Autoregressive Time Series with a Unit Root", *J*ournal of the American Statistical Association, 74.

Elliott, G., T. J. Rothenberg, and J. H. Stock (1996), "Efficient Tests for an Autoregressive Unit Root," *Econometrica*, 64.

Gorton, Gary B., Fumio Hayashi, and K. Geert Rouwenhorst (2007), "The Fundamentals of Commodity Futures Returns", *NBER Working Paper*, 13249.

Kilian, Lutz (2008a), "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *unpublished manuscript*, University of Michigan.

Kilian, Lutz (2008b), "The Economic Effects of Energy Price Shocks," *unpublished manuscript*, University of Michigan.

Mackintosh, James (2008), “Hedge funds have worst month since 2000,” *Financial Times*, July 26.

Marzo, Massimiliano, Fabrizio Spargoli, and Paolo Zagaglia (2008), “The Information Content of Oil Spreads: How Far Do They Do?,” *unpublished manuscript*, Sveriges Riksbank, January.

Mönch, Emanuel, (2005), “Forecasting the Yield Curve in a Data-Rich Environment: A No-Arbitrage Factor-Augmented VAR Approach”, *E*CB Working Paper, 544.

Phillips, P. C. B., and P. Perron (1988), “"Testing for a Unit Root in Time Series Regression”, *B*iometrika, 75,

Perron, Pierre, and Serena Ng (1996), “Useful Modifications to Unit Root Tests with Dependent Errors and Their Local Asymptotic Properties," *Review of Economic Studies*, 63.

Perron, Pierre, and Serena Ng (2001), “Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power," *Econometrica*, 69.

Sargan, J. D., and A. Bhargava (1993), “Testing for Residuals from Least Squares Regression Being Generated by Gaussian Random Walk," *Econometrica*, 51.

Stock, James H., and Mark W. Watson (2002), “Macroeconomic Forecasting Using Diffusion Indexes,” *Journal of Business and Economic Statistics*, 20, 147-162.

Trichet, Jean-Claude (2008), “Hearing at the Economic and Monetary Affairs Committee of the European Parliament,” Brussels, 25 June.

Permanent Subcommittee on Investigations (2008), “The Role of Market Speculation in Rising Oil and Gas Prices: A Need to Put the Cop Back on the Beat,” *Staff Report*, United States Senate, Committee on Homeland Security and Governmental Affairs, June 27 2006.

A Panel dataset

Series	Unit	Treatment	Source
PRICE DATA			
F.O.B. Cost of Crude Oil Imports From Angola	Nominal Dollars per Barrel	Diff, log	EIA
F.O.B. Cost of Crude Oil Imports From Colombia	Nominal Dollars per Barrel	Diff, log	EIA
F.O.B. Cost of Crude Oil Imports From Mexico	Nominal Dollars per Barrel	Diff, log	EIA
F.O.B. Cost of Crude Oil Imports From Nigeria	Nominal Dollars per Barrel	Diff, log	EIA
F.O.B. Cost of Crude Oil Imports From Saudi Arabia	Nominal Dollars per Barrel	Diff, log	EIA
F.O.B. Cost of Crude Oil Imports From United Kingdom	Nominal Dollars per Barrel	Diff, log	EIA
F.O.B. Cost of Crude Oil Imports From Venezuela	Nominal Dollars per Barrel	Diff, log	EIA
F.O.B. Cost of Crude Oil Imports From Persian Gulf	Nominal Dollars per Barrel	Diff, log	EIA
Average F.O.B. Cost of Crude Oil Imports From All OPEC	Nominal Dollars per Barrel	Diff, log	EIA
Average F.O.B. Cost of Crude Oil Imports From All Non-OPEC	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From Angola	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From Canada	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From Colombia	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From Mexico	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From Nigeria	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From Saudi Arabia	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From Venezuela	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From Persian Gulf	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From All OPEC	Nominal Dollars per Barrel	Diff, log	EIA
Landed Cost of Crude Oil Imports From All Non-OPEC	Nominal Dollars per Barrel	Diff, log	EIA
Unleaded Regular Gasoline, U.S. City Average Retail Price	Nominal Cents per Gallon	Diff, log	EIA
Unleaded Premium Gasoline, U.S. City Average Retail Price	Nominal Cents per Gallon	Diff, log	EIA
All Types of Gasoline, U.S. City Average Retail Price	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Finished Motor Gasoline to End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Finished Aviation Gasoline to End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Kerosene-Type Jet Fuel to End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Kerosene to End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of No. 2 Fuel Oil to End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of No. 2 Diesel Fuel to End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Propane (Consumer Grade) to End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Finished Motor Gasoline for Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Finished Aviation Gasoline for Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Kerosene-Type Jet Fuel for Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Kerosene for Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of No. 2 Fuel Oil for Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of No. 2 Diesel Fuel for Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Propane (Consumer Grade) for Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Residual Fuel Oil, Percent, Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Residual Fuel Oil, Percent, End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Residual Fuel Oil, Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Residual Fuel Oil, End Users	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Residual Fuel Oil, Average, Resale	Nominal Cents per Gallon	Diff, log	EIA
Refiner Price of Residual Fuel Oil, Average, End Users	Nominal Cents per Gallon	Diff, log	EIA
Shipment prices MED-UKC	doll./tonn	Diff, log	Platt's
Shipment prices GULF -WEST	doll./tonn	Diff, log	Platt's
STOCK AND FLOW DATA			
Coal Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Natural Gas Consumed by the Commercial Sector	Trillion Btu	Diff, perc. log	EIA
Petroleum Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Total Fossil Fuels Consumed by the Commercial Sector	Trillion Btu	Diff, perc. log	EIA
Hydroelectric Power Consumed by the Commercial Sector	Trillion Btu	First diff. of level	EIA
Geothermal Energy Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Biomass Energy Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Total Renewable Energy Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Primary Energy Consumed by the Commercial Sector	Trillion Btu	Diff, perc. log	EIA
Electricity Retail Sales to the Commercial Sector	Trillion Btu	Diff, perc. log	EIA
Commercial Sector Electrical System Energy Losses	Trillion Btu	Diff, perc. log	EIA
Total Energy Consumed by the Commercial Sector	Trillion Btu	Diff, perc. log	EIA
Coal Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Natural Gas Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Petroleum Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Total Fossil Fuels Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Nuclear Electric Power Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Hydroelectric Power Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Geothermal Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Solar/PV Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Wind Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Biomass Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Total Renewable Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Electric Power Sector Electricity Net Imports	Trillion Btu	Diff, perc	EIA
Primary Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Coal Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA
Natural Gas Consumed by the Residential Sector	Trillion Btu	Diff, perc. log	EIA
Petroleum Consumed by the Residential Sector	Trillion Btu	Diff, perc. log	EIA
Total Fossil Fuels Consumed by the Residential Sector	Trillion Btu	Diff, perc. log	EIA
Geothermal Energy Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA
Solar/PV Energy Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA

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Series	Unit	Treatment	Source
Biomass Energy Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA
Total Renewable Energy Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA
Primary Energy Consumed by the Residential Sector	Trillion Btu	Diff, perc. log	EIA
Electricity Retail Sales to the Residential Sector	Trillion Btu	Diff, perc. log	EIA
Residential Sector Electrical System Energy Losses	Trillion Btu	Diff, perc. log	EIA
Total Energy Consumed by the Residential Sector	Trillion Btu	Diff, perc. log	EIA
Natural Gas Consumed by the Transportation Sector	Trillion Btu	Diff, log	EIA
Petroleum Consumed by the Transportation Sector	Trillion Btu	Diff, perc. log	EIA
Total Fossil Fuels Consumed by the Transportation Sector	Trillion Btu	Diff, perc. log	EIA
Biomass Energy Consumed by the Transportation Sector	Trillion Btu	Diff, log	EIA
Primary Energy Consumed by the Transportation Sector	Trillion Btu	Diff, perc. log	EIA
Electricity Retail Sales to the Transportation Sector	Trillion Btu	Diff, log	EIA
Transportation Sector Electrical System Energy Losses	Trillion Btu	Diff, log	EIA
Total Energy Consumed by the Transportation Sector	Trillion Btu	Diff, perc. log	EIA
Crude Oil and Natural Gas Rotary Rigs in Operation, Onshore	Number of rigs	Diff, perc. log	EIA
Crude Oil and Natural Gas Rotary Rigs in Operation, Offshore	Number of rigs	Diff, perc. log	EIA
Crude Oil Rotary Rigs in Operation	Number of rigs	Diff, perc. log	EIA
Natural Gas Rotary Rigs in Operation	Number of rigs	Diff, perc. log	EIA
Crude Oil and Natural Gas Rotary Rigs in Operation, Total	Number of rigs	Diff, perc. log	EIA
Active Well Service Rig Count	Number of rigs	Diff, perc. log	EIA
Wells Drilled, Exploratory, Crude Oil	Number of wells	Diff, log	EIA
Wells Drilled, Exploratory, Natural Gas	Number of wells	Diff, log	EIA
Wells Drilled, Exploratory, Dry	Number of wells	Diff, perc. log	EIA
Wells Drilled, Exploratory, Total	Number of wells	Diff, perc. log	EIA
Wells Drilled, Development, Crude Oil	Number of wells	Diff, perc. log	EIA
Wells Drilled, Development, Natural Gas	Number of wells	Diff, perc. log	EIA
Wells Drilled, Development, Dry	Number of wells	Diff, perc. log	EIA
Wells Drilled, Development, Total	Number of wells	Diff, perc. log	EIA
Wells Drilled, Total, Crude Oil	Number of wells	Diff, perc. log	EIA
Wells Drilled, Total, Natural Gas	Number of wells	Diff, perc. log	EIA
Wells Drilled, Total, Dry	Number of wells	Diff, perc. log	EIA
Crude Oil, Natural Gas, and Dry Wells Drilled, Total	Number of wells	Diff, perc. log	EIA
Total Footage Drilled	Thousand Feet	Diff, perc. log	EIA
Hydroelectric Power Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Geothermal Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Solar/PV Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Wind Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Wood Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Waste Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Biomass Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, log	EIA
Total Renewable Energy Consumed by the Electric Power Sector	Trillion Btu	Diff, perc. log	EIA
Biodiesel Production	Trillion Btu	Diff, log	EIA
Fuel Ethanol Feedstock	Trillion Btu	Diff, log	EIA
Fuel Ethanol Losses and Co-products	Trillion Btu	Diff, log	EIA
Fuel Ethanol Production	Trillion Btu	Diff, perc. log	EIA
Fuel Ethanol Net Imports	Trillion Btu	Diff, log	EIA
Fuel Ethanol Stocks	Thousand Barrels	Diff, perc. log	EIA
Fuel Ethanol Consumption	Trillion Btu	Diff, perc. log	EIA
Hydroelectric Power Consumed by the Industrial Sector	Trillion Btu	Diff, log	EIA
Geothermal Energy Consumed by the Industrial Sector	Trillion Btu	Diff, log	EIA
Wood Energy Consumed by the Industrial Sector	Trillion Btu	Diff, perc. log	EIA
Waste Energy Consumed by the Industrial Sector	Trillion Btu	Diff, log	EIA
Fuel Ethanol Consumed by the Industrial Sector	Trillion Btu	Diff, log	EIA
Biomass Losses and Co-products in the Industrial Sector	Trillion Btu	Diff, log	EIA
Biomass Energy Consumed by the Industrial Sector	Trillion Btu	Diff, perc. log	EIA
Total Renewable Energy Consumed by the Industrial Sector	Trillion Btu	Diff, perc. log	EIA
Fuel Ethanol Consumed by the Transportation Sector	Trillion Btu	Diff, log	EIA
Biodiesel Consumed by the Transportation Sector	Trillion Btu	Diff, log	EIA
Biomass Energy Consumed by the Transportation Sector	Trillion Btu	Diff, log	EIA
Biofuels Production	Trillion Btu	Diff, log	EIA
Total Biomass Energy Production	Trillion Btu	Diff, perc. log	EIA
Total Renewable Energy Production	Trillion Btu	Diff, perc. log	EIA
Hydroelectric Power Consumption	Trillion Btu	Diff, perc. log	EIA
Geothermal Energy Consumption	Trillion Btu	Diff, log	EIA
Solar/PV Energy Consumption	Trillion Btu	Diff, log	EIA
Wind Energy Consumption	Trillion Btu	Diff, log	EIA
Wood Energy Consumption	Trillion Btu	Diff, perc. log	EIA
Waste Energy Consumption	Trillion Btu	Diff, log	EIA
Biofuels Consumption	Trillion Btu	Diff, log	EIA
Total Biomass Energy Consumption	Trillion Btu	Diff, perc. log	EIA
Total Renewable Energy Consumption	Trillion Btu	Diff, perc. log	EIA
Geothermal Energy Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA
Solar/PV Energy Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA
Wood Energy Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA
Total Renewable Energy Consumed by the Residential Sector	Trillion Btu	Diff, log	EIA
Hydroelectric Power Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Geothermal Energy Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Wood Energy Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Waste Energy Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Fuel Ethanol Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Biomass Energy Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Total Renewable Energy Consumed by the Commercial Sector	Trillion Btu	Diff, log	EIA
Asphalt and Road Oil Product Supplied	Trillion Btu	Diff, perc. log	EIA
Aviation Gasoline Product Supplied	Trillion Btu	Diff, log	EIA
Distillate Fuel Oil Product Supplied	Trillion Btu	Diff, perc. log	EIA
Jet Fuel Product Supplied	Trillion Btu	Diff, perc. log	EIA
Kerosene Product Supplied	Trillion Btu	Diff, perc	EIA
Propane/Propylene Product Supplied	Trillion Btu	Diff, perc. log	EIA

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Series	Unit	Treatment	Source
Liquefied Petroleum Gases Product Supplied	Trillion Btu	Diff, perc. log	EIA
Lubricants Product Supplied	Trillion Btu	Diff, log	EIA
Motor Gasoline Product Supplied	Trillion Btu	Diff, perc. log	EIA
Petroleum Coke Product Supplied	Trillion Btu	Diff, log	EIA
Residual Fuel Oil Product Supplied	Trillion Btu	Diff, perc. log	EIA
Other Petroleum Products Supplied	Trillion Btu	Diff, perc. log	EIA
Total Petroleum Products Supplied	Trillion Btu	Diff, perc. log	EIA
Crude Oil Imports, Total	Thousand Barrels per Day	Diff, perc. log	EIA
Distillate Fuel Oil Imports	Thousand Barrels per Day	Diff, perc. log	EIA
Jet Fuel Imports	Thousand Barrels per Day	Diff, perc. log	EIA
Propane/Propylene Imports	Thousand Barrels per Day	Diff, perc. log	EIA
Liquefied Petroleum Gases Imports	Thousand Barrels per Day	Diff, perc. log	EIA
Finished Motor Gasoline Imports	Thousand Barrels per Day	Diff, perc. log	EIA
Residual Fuel Oil Imports	Thousand Barrels per Day	Diff, perc. log	EIA
Other Petroleum Products Imports	Thousand Barrels per Day	Diff, perc. log	EIA
Total Petroleum Imports	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Exports	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Products Exports	Thousand Barrels per Day	Diff, perc. log	EIA
Total Petroleum Exports	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Persian Gulf	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Canada	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, China	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Egypt	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Mexico	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Norway	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Russia	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, United Kingdom	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, United States	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Total Non-OPEC	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, World	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Algeria	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Angola	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Ecuador	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Indonesia	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Iran	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Iraq	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Kuwait	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Libya	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Nigeria	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Qatar	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Saudi Arabia	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, United Arab Emirates	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, Venezuela	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Production, OPEC	Thousand Barrels per Day	Diff, perc. log	EIA
Crude Oil Stocks, SPR	Million Barrels	Diff, perc. log	EIA
Crude Oil Stocks, Non-SPR	Million Barrels	Diff, perc. log	EIA
Crude Oil Stocks, Total	Million Barrels	Diff, perc. log	EIA
Distillate Fuel Oil Stocks	Million Barrels	Diff, perc. log	EIA
Jet Fuel Stocks	Million Barrels	Diff, log	EIA
Propane/Propylene Stocks	Million Barrels	Diff, log	EIA
Liquefied Petroleum Gases Stocks	Million Barrels	Diff, perc. log	EIA
Motor Gasoline Stocks	Million Barrels	Diff, perc. log	EIA
Residual Fuel Oil Stocks	Million Barrels	Diff, log	EIA
Other Petroleum Products Stocks	Million Barrels	Diff, perc. log	EIA
Total Petroleum Stocks	Million Barrels	Diff, perc. log	EIA
Crude Oil Refinery Net Input	Thousand Barrels per Day	Diff, perc. log	EIA
Natural Gas Plant Liquids Refinery and Blender Net Inputs	Thousand Barrels per Day	Diff, perc. log	EIA
Other Liquids Refinery and Blender Net Inputs	Thousand Barrels per Day	Diff, perc. log	EIA
Total Petroleum Refinery and Blender Net Inputs	Thousand Barrels per Day	Diff, perc. log	EIA
Distillate Fuel Oil Refinery Net Production	Thousand Barrels per Day	Diff, perc. log	EIA
Jet Fuel Refinery Net Production	Thousand Barrels per Day	Diff, perc. log	EIA
Propane/Propylene Refinery Net Production	Thousand Barrels per Day	Diff, perc. log	EIA
Liquefied Petroleum Gases Refinery Net Production	Thousand Barrels per Day	Diff, perc. log	EIA
Finished Motor Gasoline Refinery and Blender Net Production	Thousand Barrels per Day	Diff, perc. log	EIA
Residual Fuel Oil Refinery Net Production	Thousand Barrels per Day	Diff, perc. log	EIA
Other Petroleum Products Refinery Net Production	Thousand Barrels per Day	Diff, perc. log	EIA
Total Petroleum Refinery and Blender Net Production	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, France	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, Germany	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, Italy	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, United Kingdom	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, OECD Europe	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, Canada	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, Japan	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, South Korea	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, United States	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, Other OECD	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Consumption, Total OECD	Thousand Barrels per Day	Diff, perc. log	EIA
Petroleum Stocks, France	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, Germany	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, Italy	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, United Kingdom	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, OECD Europe	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, Canada	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, Japan	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, South Korea	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, United States	Million Barrels	Diff, perc. log	EIA
Petroleum Stocks, Other OECD	Million Barrels	Diff, perc. log	EIA

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Series	Unit	Treatment	Source
Petroleum Stocks, Total OECD	Million Barrels	Diff, perc. log	EIA
MACROECONOMIC AND FINANCIAL DATA			
Yield on 10 year Gov US bonds	percent	Diff, log	DS
M1	billion dollars	Diff, log	DS
M2	billion dollars	Diff, log	DS
US Bank lending rate	percent	Diff, log	DS
Capital utilization rate	percentage index	Diff, log	DS
US confidence index rate	index	Diff, log	DS
Producer's price index for finished goods	index	Diff, log	DS
Producer's price index less food and energy	index	Diff, log	DS
Federal Funds rate	percent	Diff, log	DS
Consumption expenditure US	billion dollars	Diff, log	DS
US CPI index	index	Diff, log	DS
US industrial production index	index	Diff, log	DS
US house construction index	index	Diff, log	DS
Yield on 20years US gov. Bonds	percent	Diff, log	DS
Dow Jones index	index	Diff, log	DS
Sp500 index	index	Diff, log	DS
Yield on US 3yaers gov bonds	percent	Diff, log	DS
Crude ligh 1 month open interest	number of contracts	Diff, log	DS
Crude light volume front month	number of contracts	Diff, log	DS
Crude ligh 3 month open interest	number of contracts	Diff, log	DS
Crude light volume3 month	number of contracts	Diff, log	DS
Crude ligh 6 month open interest	number of contracts	Diff, log	DS
Crude light volume6 month	number of contracts	Diff, log	DS
Crude ligh 12 month open interest	number of contracts	Diff, log	DS
Crude light volume 12 month	number of contracts	Diff, log	DS
Share price of Total	average price	Diff, log	DS
Share price of Exxon	average price	Diff, log	DS
Share price of BP	average price	Diff, log	DS
Share price of CONOCO	average price	Diff, log	DS
Share price of Shell	average price	Diff, log	DS
Share price of Chevron	average price	Diff, log	DS
JPMorgan global index	index	Diff, log	DS
JPMorgan global Eurobond idex	index	Diff, log	DS
JPMorgna US gov bond index	price	Diff, log	DS
Crude Spread WTI- Brent M+1 NY Cls	price	Diff, log	DS
Crude Spread WTI- Brent M+2 NY Cls	price	Diff, log	DS
Crude Spread Dubai M-M+1 NY Close	price	Diff, log	DS
Crude Spread Dubai M+1-M+2 NY Close	price	Diff, log	DS
Crude Oil-Dtd Brent UK Close USD/BBL	price	Diff, log	DS
Crude Oil-Brent 1Mth Fwd FOB USD/BBL	price	Diff, log	DS
US TREASURY BILL RATE - 3 MONTH (EP)	percent	Diff, log	DS
USD to EURO noon NY (EP) NADJ	exchange rate	Diff, log	DS
Morgan Stanley total index	index	Diff, log	DS
US-DS index Oil & Gas - PRICE INDEX	index	Diff, log	DS
Citigroup Bond Index Corporate US	index	Diff, log	DS
Citigroup Bond Index Overall	index	Diff, log	DS
Citigroup Bond index treasury	index	Diff, log	DS
Citigroup bond Index Corporate Bond 1-3 years, Euro area	index	Diff, log	DS
Citigroup Bond Index Total Return index	index	Diff, log	DS
Citigroup Bond Index Industrial	index	Diff, log	DS
Citigroup Bond Corporate Industrial Worldwide index	index	Diff, log	DS
DAX stock market index	index	Diff, log	DS
UK stock market index	index	Diff, log	DS
China Industrial production index	index	Diff, log	DS
Euro area industrial production index	index	Diff, log	DS
USD-GBP exchange rate	exchange rate	Diff, log	DS
UK industrial production index	index	Diff, log	DS
World Dow-Jones industrial performance	index	Diff, log	DS
CBOE VIX (implied volatility index)	index	Diff, log	DS
BS 1M	index	Diff, log	ECB
BS 3M	index	Diff, log	ECB
BS 6M	index	Diff, log	ECB
BS 1Y	index	Diff, log	ECB
NYMEX Natural gas 1 month	price	Diff, log	DS
NYMEX Natural gas 3 month	price	Diff, log	DS
NYMEX Natural gas 6 month	price	Diff, log	DS
NYMEX Heating oil 1 month	price	Diff, log	DS
NYMEX Heating oil 3 month	price	Diff, log	DS

Legend:
EIA: Energy Information Administration.
DS: Datastream
ECB: European Central Bank
Diff: first difference of level.
Diff, log: first difference of log.
Diff, perc: first difference of percentage value.
Diff, perc. log: first difference of log of percentage value.

Table 1: Variance explained by the factors

Factor	R^2	First autocorr. coeff.
1	0.1823	0.3241
2	0.3065	-0.4735
3	0.3961	0.4727
4	0.4758	0.1521

Table 2: Share of explained variance of highly-correlated series

Factor 1 (18% to total variance)	R^2
Landed Cost of Crude Oil Imports From All Non-OPEC Countries	0.85
Average F.O.B. Cost of Crude Oil Imports From All Non-OPEC Countries	0.83
Refiner Price of No. 2 Diesel Fuel for Resale	0.80
Landed Cost of Crude Oil Imports From Mexico	0.80
Refiner Price of No. 2 Diesel Fuel to End Users	0.79
Factor 2 (12% to total variance)	
Motor Gasoline Stocks (Including Blending Components and Gasohol)	0.84
Volume of Crude Oil Futures 3-Month Contracts	0.46
Other Petroleum Products Stocks	0.38
Finished Motor Gasoline Imports	0.31
Petroleum Stocks, Other OECD	0.27
Factor 3 (9% to total variance)	
Propane/Propylene Product Supplied	0.31
Refiner Price of Kerosene to End Users	0.18
Liquefied Petroleum Gases Product Supplied	0.17
Refiner Price of Propane (Consumer Grade) for Resale	0.12
Refiner Price of Kerosene for Resale	0.11
Factor 4 (8% to total variance)	
Open Interest on 12-Month Crude Oil Futures	0.19
Open Interest on 6-Month Crude Oil Futures	0.18
Jet Fuel Refinery Net Production	0.17
Total Petroleum Refinery and Blender Net Inputs	0.17
Volume 6-Month Crude Oil Futures	0.15

Legend: This table reports R^2 of univariate regressions of factors on macro variables. I report the five variables with the highest correlation with the factors.

Table 3: Correlations between factors and returns

	Factor 1	Factor 2	Factor 3	Factor 4
	(a) Contemporaneous correlation			
1-month	0.896	-0.129	-0.019	0.109
3-month	0.887	-0.143	-0.023	0.119
6-month	0.859	-0.085	-0.126	0.111
12-month	0.299	-0.079	-0.051	0.122
	(b) Correlation with 1-month lagged factors			
1-month	0.146	0.067	0.015	0.187
3-month	0.153	0.071	0.018	0.182
6-month	0.202	0.017	-0.056	0.096
12-month	0.144	-0.093	-0.131	0.0006
	(c) Correlation with 6-month lagged factors			
1-month	-0.005	-0.009	0.154	0.015
3-month	0.005	-0.001	0.154	0.014
6-month	0.049	0.041	0.143	0.049
12-month	-0.035	0.084	0.033	0.180

Table 4: Unrestricted regressions of yields on factors

	1-month	3-month	6-month	12-month
Factor 1	0.887 [0.030]	0.900 [0.029]	0.859 [0.036]	0.298 [0.067]
Factor 2	−0.143 [0.035]	−0.133 [0.028]	−0.084 [0.035]	−0.079 [0.068]
Factor 3	−0.023 [0.029]	−0.068 [0.031]	−0.126 [0.033]	−0.050 [0.069]
Factor 4	0.119 [0.031]	0.098 [0.029]	0.110 [0.035]	0.122 [0.069]
R^2	0.823	0.843	0.774	0.113

Legend: Brackets report standard errors. Constants are omitted.

Table 5: Unit-root tests

	Yields				Factors			
	1-month	3-month	6-month	12-month	1	2	3	4
Phillips-Perron Mz_α	-94.742	-94.908	-93.516	-42.113	-122.625	-16.542	-20.005	-15.260
Phillips-Perron Mz_t	-6.881	-6.888	-6.836	-4.586	-7.830	-2.679	-2.888	-2.871
Sargan-Bhargava	0.072	0.097	0.072	0.108	0.064	0.056	0.144	0.126
Mod. point-optimal	0.260	0.258	0.266	0.588	0.199	0.329	1.033	0.837

Legend: The auxiliary models include a constant. The lag lengths are chosen using the modified BIC dicussed in Perron and Ng (2001). The modified Phillips-Perron are all outlined in Perron and Ng (1996), the point-optimal test is from Elliott, Rothenberg, and Stock (1996) and is amended in Perron and Ng (2001) together with Sargan and Bhargava (1983)'s test. All the test statistics are significant at the 5% level.

Table 6: Parameter estimates of the FAVAR model

	Γ_1							
Factor 1	0.657 [0.193]	-0.120 [0.086]	0.073 [0.079]	0.208 [0.071]	0.279 [0.629]	-0.496 [0.635]	-0.101 [0.192]	0.086 [0.083]
Factor 2	$-.0004$ [0.158]	-0.583 [0.071]	-0.036 [0.065]	-0.224 [0.058]	-0.194 [0.517]	0.459 [0.521]	-0.446 [0.156]	0.123 [0.068]
Factor 3	-0.387 [0.174]	-0.096 [0.078]	0.571 [0.072]	0.161 [0.064]	0.874 [0.569]	-0.680 [0.575]	-0.0008 [0.175]	0.009 [0.075]
Factor 4	-0.243 [0.195]	-0.018 [0.087]	-0.031 [0.081]	0.126 [0.072]	0.302 [0.636]	-0.203 [0.642]	-0.016 [0.195]	-0.010 [0.083]
1-month	0.588 [0.207]	-0.016 [0.092]	0.065 [0.086]	0.225 [0.076]	0.632 [0.675]	-0.962 [0.681]	-0.141 [0.206]	0.085 [0.089]
3-month	0.566 [0.204]	-0.002 [0.091]	0.062 [0.084]	0.220 [0.075]	1.315 [0.666]	-1.639 [0.672]	-0.118 [0.204]	0.084 [0.087]
6-month	0.534 [0.211]	-0.032 [0.094]	-0.042 [0.087]	0.126 [0.078]	0.798 [0.687]	-0.889 [0.693]	-0.194 [0.211]	-0.083 [0.091]
12-month	0.311 [0.186]	-0.061 [0.083]	-0.088 [0.077]	0.043 [0.068]	-0.476 [0.607]	0.169 [0.612]	0.382 [0.186]	-0.523 [0.081]

	Γ_2							
Factor 1	-0.319 [−0.014]	0.031 [0.079]	-0.223 [0.080]	0.049 [0.072]	0.976 [0.636]	-0.953 0.631]	0.097 [0.196]	-0.081 [0.085]
Factor 2	-0.015 [0.138]	-0.145 [0.064]	0.156 [0.066]	0.322 [0.052]	0.168 [0.523]	-0.031 [0.518]	-0.414 [0.161]	0.027 [0.070]
Factor 3	-0.167 [0.152]	-0.327 [0.071]	-0.144 [0.072]	-0.081 [0.065]	0.511 [0.576]	-0.160 [0.571]	-0.056 [0.178]	-0.034 [0.078]
Factor 4	0.228 [0.170]	-0.221 [0.079]	0.405 [0.081]	-0.009 [0.073]	-0.966 [0.643]	0.689 [0.637]	0.064 [0.199]	-0.061 [0.087]
1-month	-0.131 [0.181]	0.064 [0.084]	-0.234 [0.085]	0.048 [0.077]	1.179 [0.682]	-1.261 [0.676]	0.072 [0.211]	-0.067 [0.091]
3-month	-0.141 [0.178]	0.076 [0.083]	-0.222 [0.087]	0.044 [0.076]	1.493 [0.673]	-1.607 [0.667]	0.119 [0.208]	-0.070 [0.091]
6-month	-0.328 [0.184]	0.054 [0.086]	-0.158 [0.087]	0.017 [0.079]	1.212 [0.695]	-1.118 [0.689]	0.170 [0.215]	-0.182 [0.094]
12-month	0.038 [0.162]	-0.102 [0.076]	-0.059 [0.077]	0.052 [0.069]	-0.079 [0.614]	0.081 [0.609]	0.021 [0.190]	-0.460 [0.083]

	Σ							
Factor 1	0.797							
Factor 2	-0.029	0.538						
Factor 3	0.002	-0.072	0.653					
Factor 4	0.138	-0.026	-0.116	0.815				
1-month	0.774	-0.117	-0.029	0.225	0.916			
3-month	0.759	-0.122	-0.036	0.234	0.899	0.893		
6-month	0.764	-0.074	-0.105	0.226	0.855	0.850	0.951	
12-month	0.288	-0.045	0.014	0.144	0.322	0.319	0.390	0.742

Legend: Brackets report standard errors. Constants are omitted.

Table 7: Pairwise Granger-causality F tests

	Factor 1	Factor 2	Factor 3	Factor 4
	does not Granger-cause			
1-month	2.685 (0.071)	0.405 (0.667)	3.913 (0.022)	3.405 (0.035)
3-month	3.661 (0.028)	0.450 (0.638)	3.794 (0.024)	3.139 (0.046)
6-month	3.717 (0.026)	0.039 (0.962)	1.879 (0.155)	1.245 (0.204)
12-month	15.351 ($7e{-7}$)	1.789 (0.169)	2.727 (0.068)	0.831 (0.437)

	1-month	3-month	6-month	12-month
	does not Granger-cause			
Factor 1	0.281 (0.756)	0.100 (0.905)	1.065 (0.347)	2.381 (0.095)
Factor 2	6.512 (0.002)	6.550 (0.002)	12.584 ($7e{-6}$)	2.521 (0.083)
Factor 3	2.214 (0.112)	2.475 (0.009)	1.729 (0.180)	0.524 (0.592)
Factor 4	1.833 (0.162)	1.901 (0.152)	2.937 (0.055)	2.040 (0.132)

Legend: This table reports pairwise F statistics and their p-values (in brackets).

Table 8: Out-of-sample forecasts: RMSEs

Horizon	1-month	3-month	6-month	12-month	1-month	3-month	6-month	12-month
	(a) FAVAR				(b) VAR with yields only			
1	1.0353	1.0395	1.1015	1.1642	1.0514	1.0651	1.0787	1.1898
2	1.0161	1.0215	1.0628	1.1268	1.0209	1.0272	1.0709	1.1267
3	0.9732	0.9844	1.0321	1.0997	0.9742	0.9865	1.0191	1.1108
4	0.9809	0.9931	1.0379	1.1159	0.9807	0.9953	1.0301	1.1184
5	0.9760	0.9890	1.0376	1.1169	0.9761	0.9907	1.0309	1.1226
6	0.9849	0.9978	1.0455	1.1242	0.9848	0.9996	1.0383	1.1302
	(c) Factor-only model				(d) Random walk			
1	0.7305	0.7162	0.7292	1.6776	1.4550	1.4833	1.5277	0.6941
2	0.6564	0.6437	0.6318	1.4703	1.5684	1.6054	1.6961	0.7690
3	0.6898	0.6543	0.6454	1.5050	1.4142	1.5073	1.6014	0.7315
4	0.6949	0.6848	0.6784	1.5587	1.4124	1.4507	1.5303	0.7157
5	0.7905	0.7842	0.7736	1.7813	1.2353	1.2614	1.3414	0.6270
6	0.6557	0.6391	0.6331	1.4641	1.5023	1.5614	1.6513	0.7678

Legend: This table reports the root mean squared errors of out-of-sample forecasts at various horizons.

Table 9: Out-of-sample forecasts: RMSEs relative to a random walk

Horizon	1-month	3-month	6-month	12-month	1-month	3-month	6-month	12-month
	(a) FAVAR				(b) VAR with yields only			
1	0.7115	0.7008	0.7210	1.6772	0.7226	0.7181	0.7061	1.7141
2	0.6479	0.6363	0.6266	1.4653	0.6509	0.6398	0.6314	1.4652
3	0.6882	0.6531	0.6445	1.5034	0.6889	0.6545	0.6364	1.5185
4	0.6945	0.6845	0.6783	1.5592	0.6944	0.6861	0.6731	1.5627
5	0.7901	0.7840	0.7735	1.7812	0.7901	0.7854	0.7685	1.7903
6	0.6556	0.6390	0.6331	1.4641	0.6556	0.6402	0.6288	1.4720
	(c) Factor-only model							
1	0.7305	0.7162	0.7292	1.6776				
2	0.6564	0.6437	0.6318	1.4703				
3	0.6898	0.6543	0.6454	1.5050				
4	0.6949	0.6848	0.6784	1.5587				
5	0.7905	0.7842	0.7736	1.7813				
6	0.6557	0.6391	0.6331	1.4641				

Legend: This table reports the root mean squared errors of out-of-sample forecasts relative to the random-walk forecast.

Figure 1: Estimated factors and correlated series

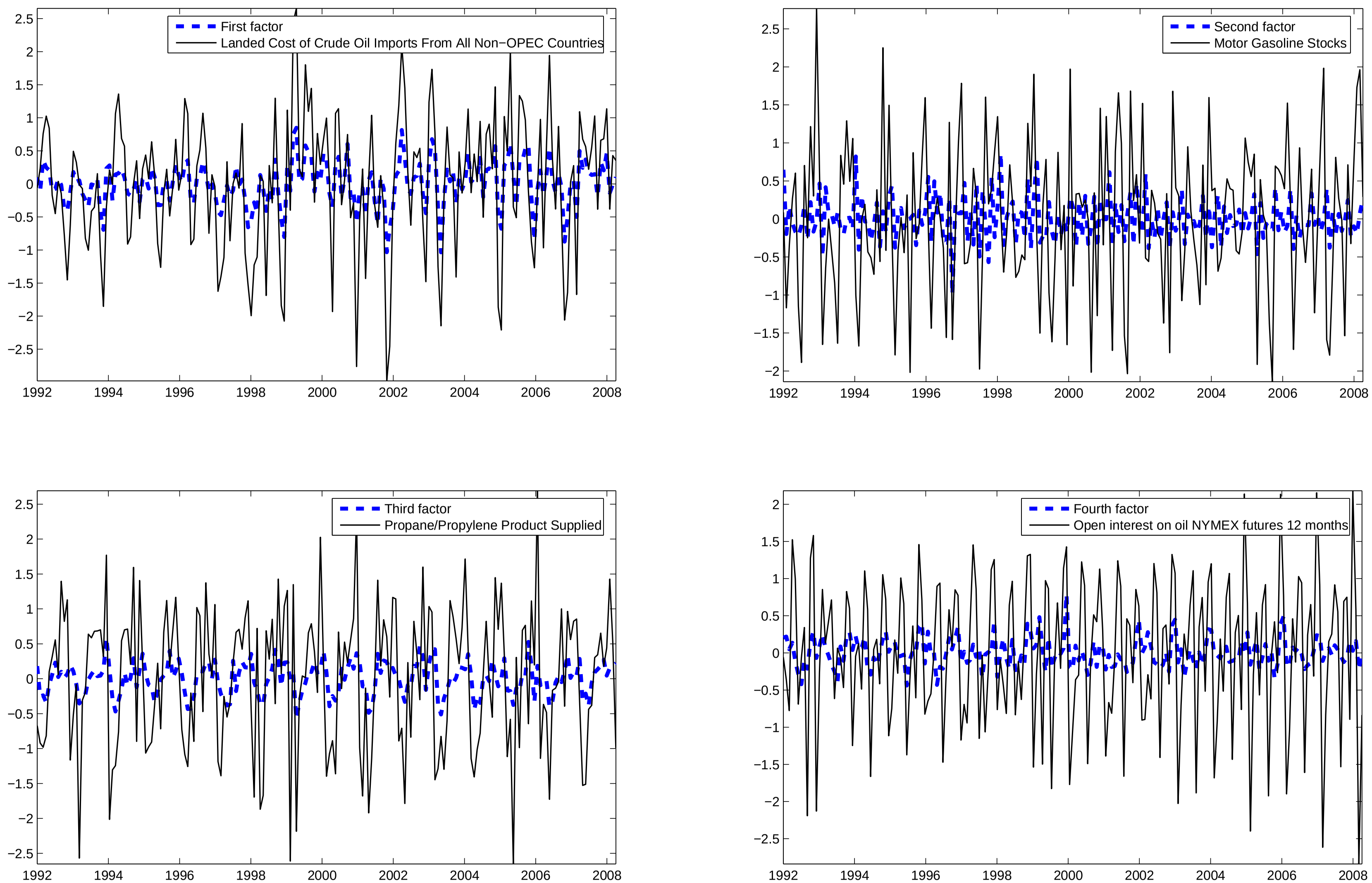
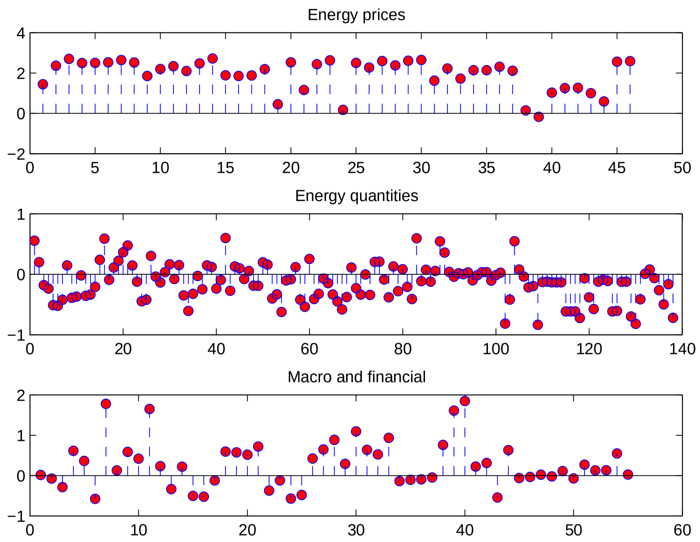
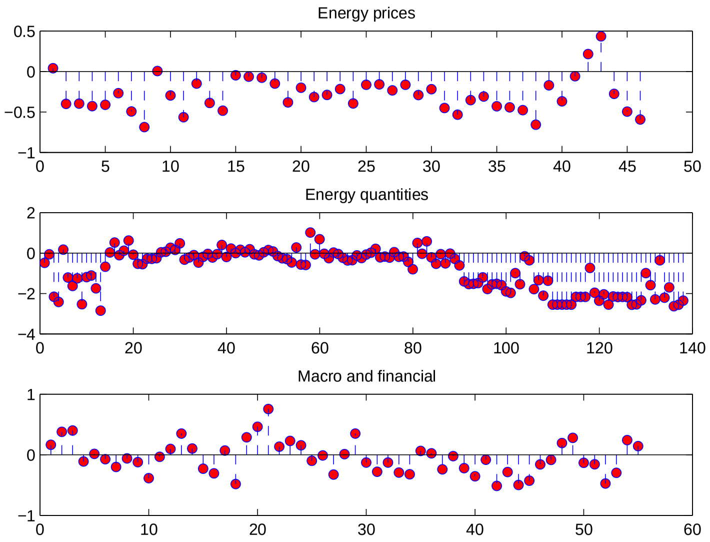


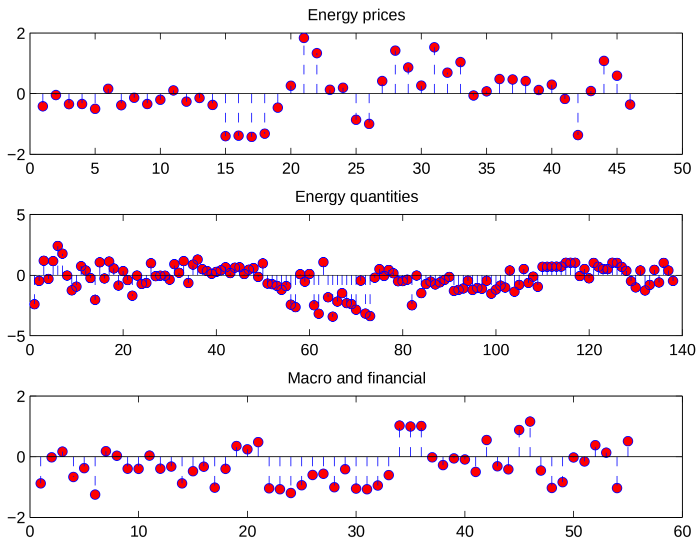
Figure 2: Factor loadings for types of data series in the panel



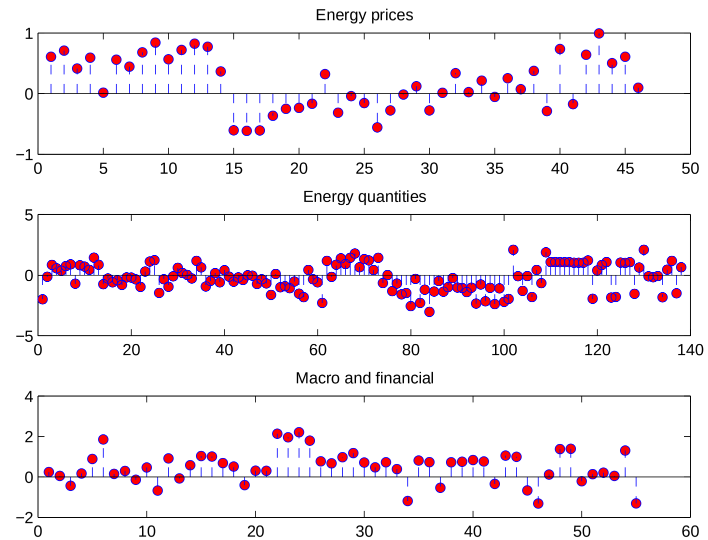
(a) First factor



(b) Second factor



(c) Third factor



(d) Fourth factor

Figure 3: Observed and model-implied yields